AIRS humidity retrievals assimilation with an ensemble Kalman filter, & Observation impact study without adjoint model

— AIRS science team meeting

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Outline

- Review of AIRS temperature retrievals assimilation results (Li et al., 2007)
- Assimilation of additional AIRS humidity retrievals on the above system
  — Improved analyses on both humidity and wind fields
- Estimating observation impact without adjoint model
  — Derivation of the formula
  — Comparison between the ensemble sensitivity method and the adjoint method (Langland and Baker, 2004)
- Future plans

NOTE: all AIRS retrievals were provided by *Chris Barnet and his students*

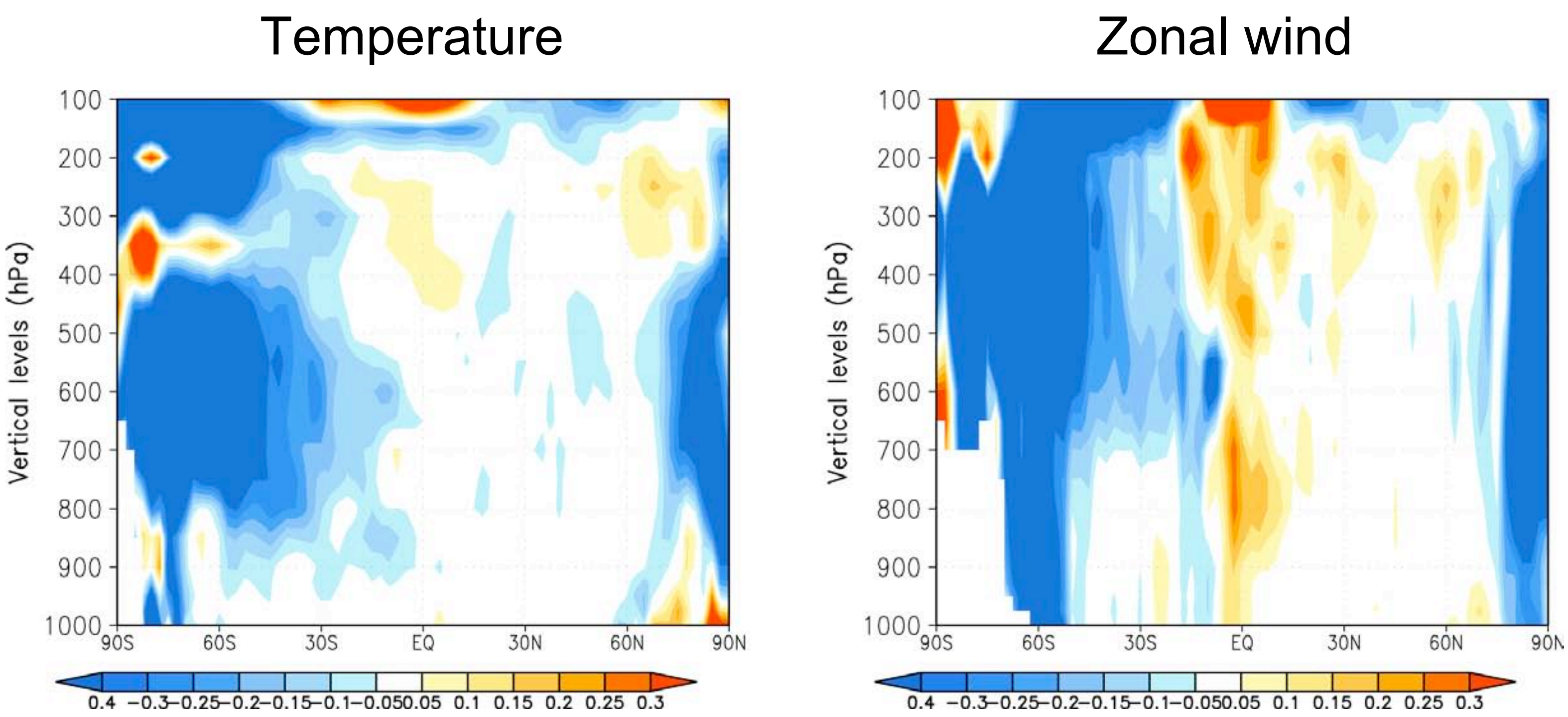
Assimilation of AIRS temperature retrievals

- *System :* NCEP GFS (T62L28) with 4D-Local Ensemble Transform Kalman Filter (4D-LETKF, Hunt et al., 2007, Szunyogh et al., 2007)
- *Experimental design:*

Experiments	*Observations*
Control run	Non-radiance operational observation data
AIRS T run	Non-radiance + AIRS temperature retrievals

- *Verification:* Operational NCEP analysis at T254L64, assimilating all operational observations. (Not "truth"!).

Zonal average analysis RMS error difference between AIRS T run and control run



Blue means AIRS run is better, Red means AIRS is worse

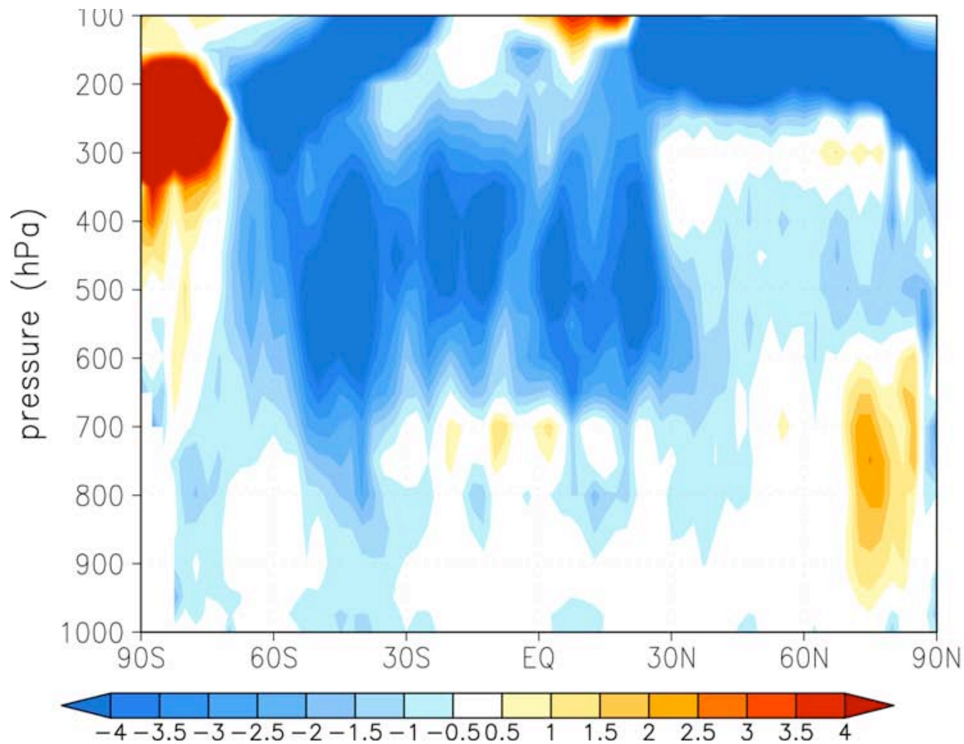
AIRS Temperature retrievals have significant positive impact in both NH and SH, and little impact on the tropics.

Assimilation of AIRS humidity retrievals on NCEP GFS with the LETKF

Experiments	*Observations*
Control run	Non-radiance + AIRS T retrievals
AIRS q run	Non-radiance + AIRS T + q retrievals

- Assimilating pseudo-RH ($\frac{q^o}{q^b_{st}}$, Dee and da Silva, 2003)
  — more Gaussian than q (assimilating of q makes u, v, t, Ps worse)
  — have no correlation with T observations (unlike relative humidity)
- Fully coupled error covariance with u, v, T, ps during data assimilation (multivariate)
- *Verification*: Operational NCEP analysis at T254L64, assimilating all operational observationsn *(not truth!)*.

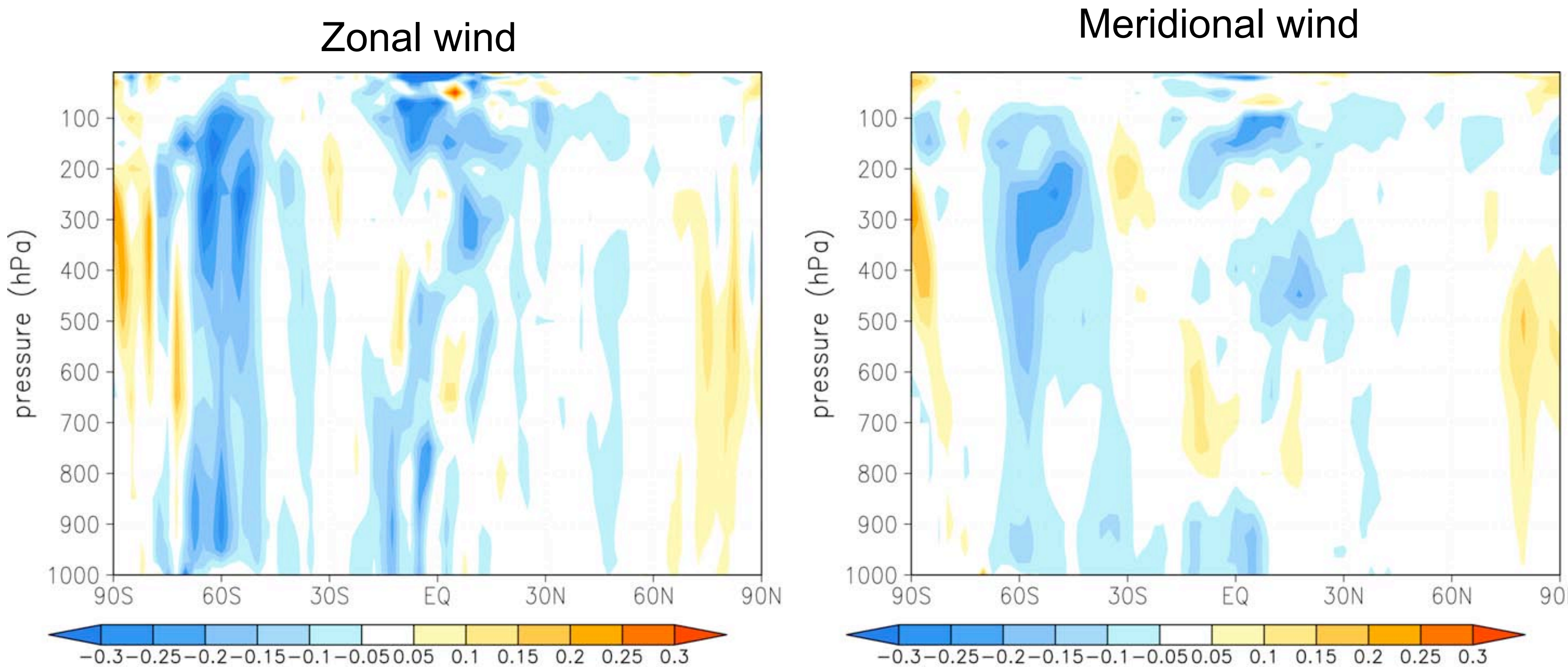
Relative humidity RMS error difference between AIRS q run and control run



Blue means AIRS run is better, Red means AIRS is worse

- Positive impact in most of the area

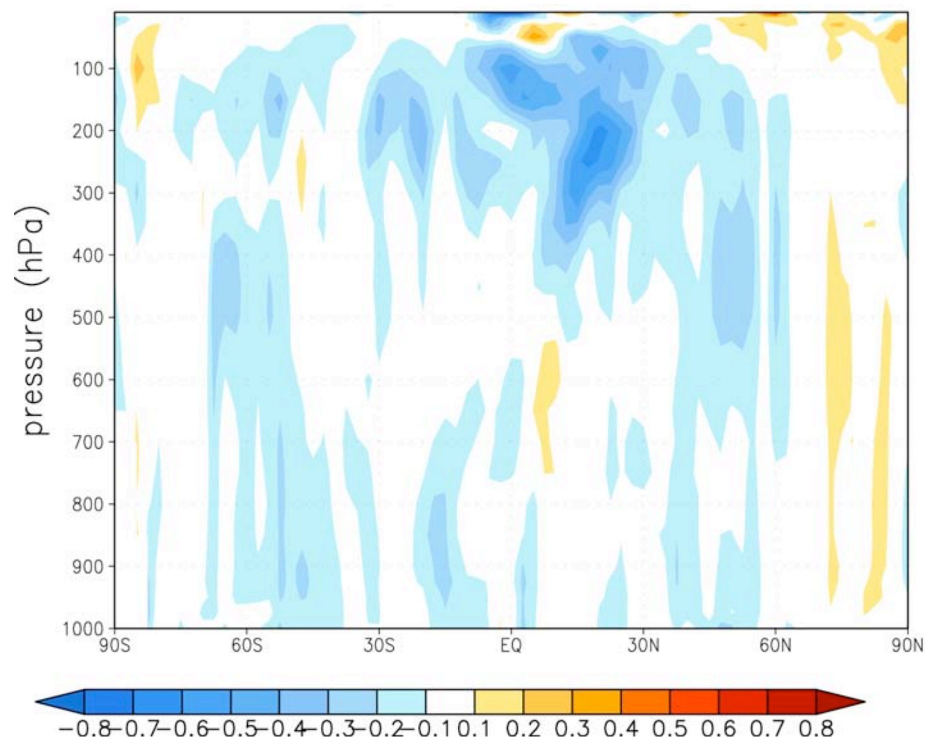
RMS error difference between humidity run and control run



- Positive impacts on both zonal wind the meridional wind.

48hr zonal wind forecast RMS error difference between humidity run and control run

Zonal wind



48-hour forecast keeps the advantage of assimilating humidity retrievals.

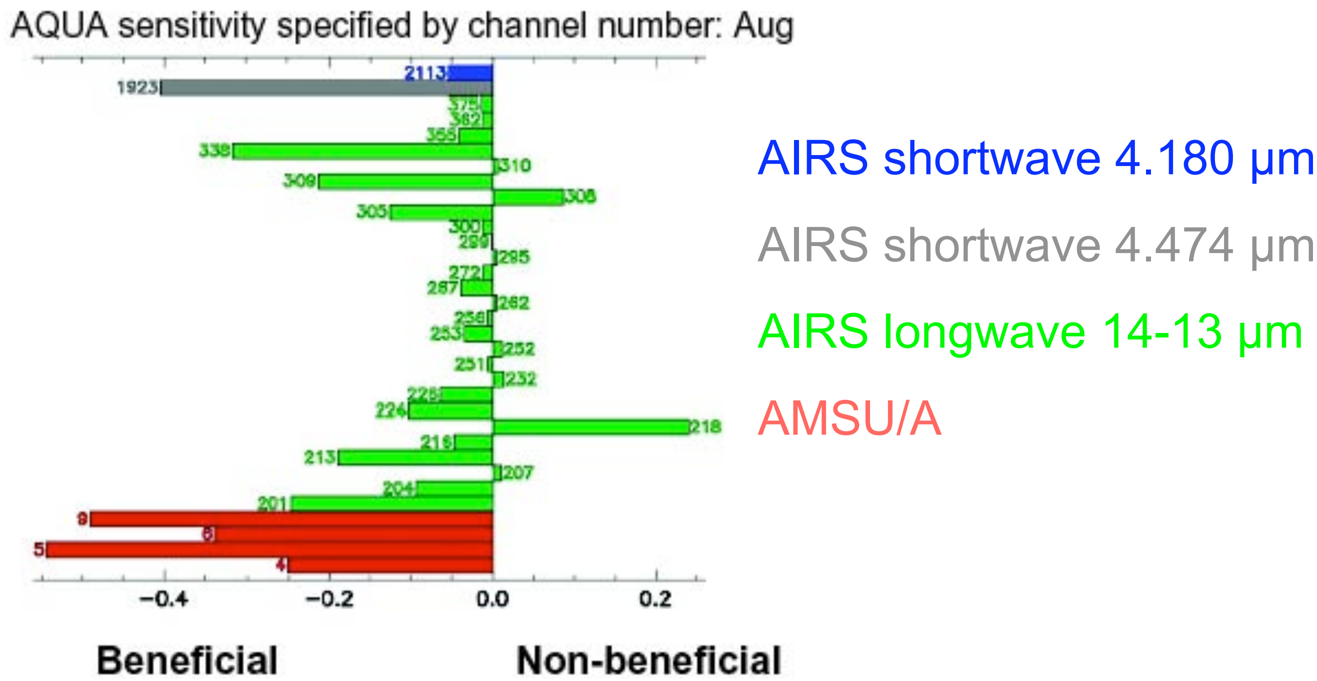
The center of larger improvement moves northward.

Summary of AIRS retrieval assimilation

- *Improved analysis accuracy from assimilating both AIRS temperature retrievals and humidity retrievals.*
- *With pseudo-RH assimilation, it improves not only humidity analysis, but also wind analysis.*
- *As far as we know, this is the first time that multivariate assimilation of humidity has been shown to improve wind fields.*

Observation impact without adjoint model

Background



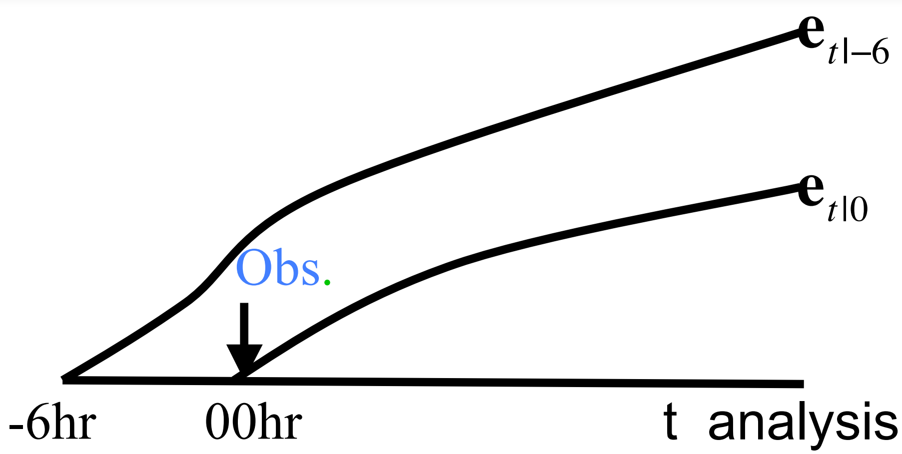
- The adjoint method (Langland and Baker, 2004; Zhu and Gelaro,2007) quantifies the reduction in forecast error for each individual observation source
- The adjoint method detects the observations which make the forecast worse.
- The adjoint method requires an adjoint model which is difficult to create.

Objective and outline

- **Objective**
  - Propose an ensemble sensitivity method to calculate observation impact without using adjoint model.

- **Outline**
  - Illustrate and derive the ensemble sensitivity method;
  - With Lorenz-40 variable model, compare the ensemble sensitivity method with adjoint method in
    a) the ability to represent the actual error reduction;
    b) the ability to detect the poor quality observations.

Schematic of the observation impact on the reduction of forecast error



$$\mathbf{e}_{t|-6} = \overline{\mathbf{x}}^f_{t|-6} - \overline{\mathbf{x}}^a_t$$

$$\mathbf{e}_{t|0} = \overline{\mathbf{x}}^f_{t|0} - \overline{\mathbf{x}}^a_t$$

(Adapted from Langland and Baker, 2004)

The only difference between $\mathbf{e}_{t|0}$ and $\mathbf{e}_{t|-6}$ is the assimilation of observations at 00hr.

Observation impact on the reduction of forecast error: $J = \frac{1}{2}(\mathbf{e}^T_{t|0}\mathbf{e}_{t|0} - \mathbf{e}^T_{t|-6}\mathbf{e}_{t|-6})$

The ensemble sensitivity method

Euclidian cost function: $J = \frac{1}{2}(\mathbf{e}_{t|0}^T \mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^T \mathbf{e}_{t|-6}) \quad \mathbf{v}_0 = \mathbf{y}_0^o - h(\overline{\mathbf{x}}_{0|-6}^b)$

Cost function as function of obs. increments: $J = \left\langle \mathbf{v}_0, \frac{\partial J}{\partial \mathbf{v}_0} \right\rangle$

The ensemble sensitivity method

Euclidian cost function: $J = \frac{1}{2}(\mathbf{e}_{t|0}^T \mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^T \mathbf{e}_{t|-6})$ $\mathbf{v}_0 = \mathbf{y}_0^o - h(\overline{\mathbf{x}}_{0|-6}^b)$

Cost function as function of obs. Increments: $J = \left\langle \mathbf{v}_0, \frac{\partial J}{\partial \mathbf{v}_0} \right\rangle$

The sensitivity of cost function with respect to the assimilated observations:

$$\frac{\partial J}{\partial \mathbf{v}_0} = \left[\tilde{\mathbf{K}}_0^T \mathbf{X}_{t|-6}^{fT} \right] \left[\mathbf{e}_{t|-6} + \mathbf{X}_{t|-6}^f \tilde{\mathbf{K}}_0 \mathbf{v}_0 \right]$$

The ensemble sensitivity method

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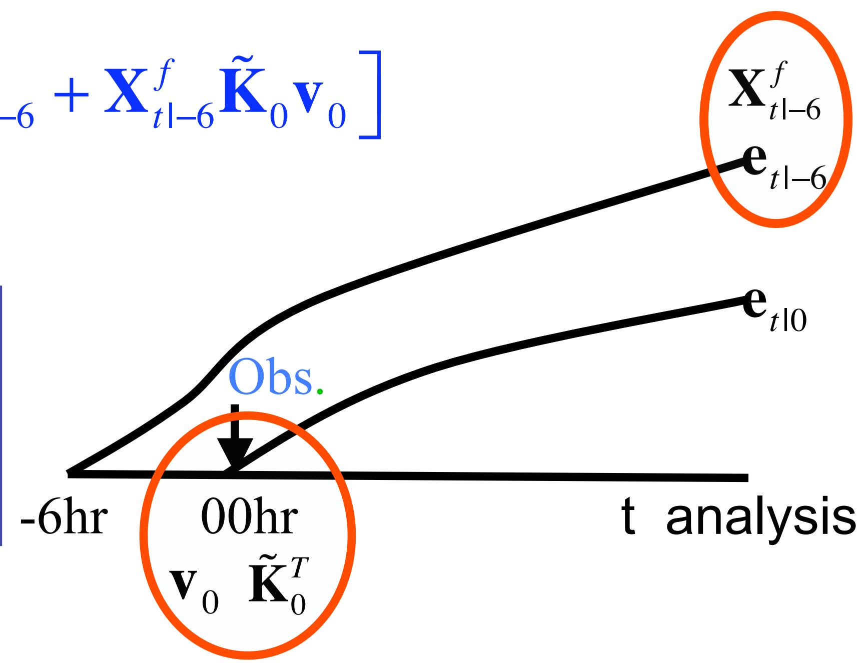


Once an independent verification is available, all this can be computed within an EnKF and does not require adjoint model

The ensemble sensitivity method

Forecast error reduction due to assimilation of observations at 00hr:

$$J = \frac{1}{2}(\mathbf{e}_{t|0}^{T}\mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^{T}\mathbf{e}_{t|-6}) = \left\langle \mathbf{v}_0, \frac{\partial J}{\partial \mathbf{v}_0} \right\rangle$$

Sensitivity of forecast error to assimilated observations:

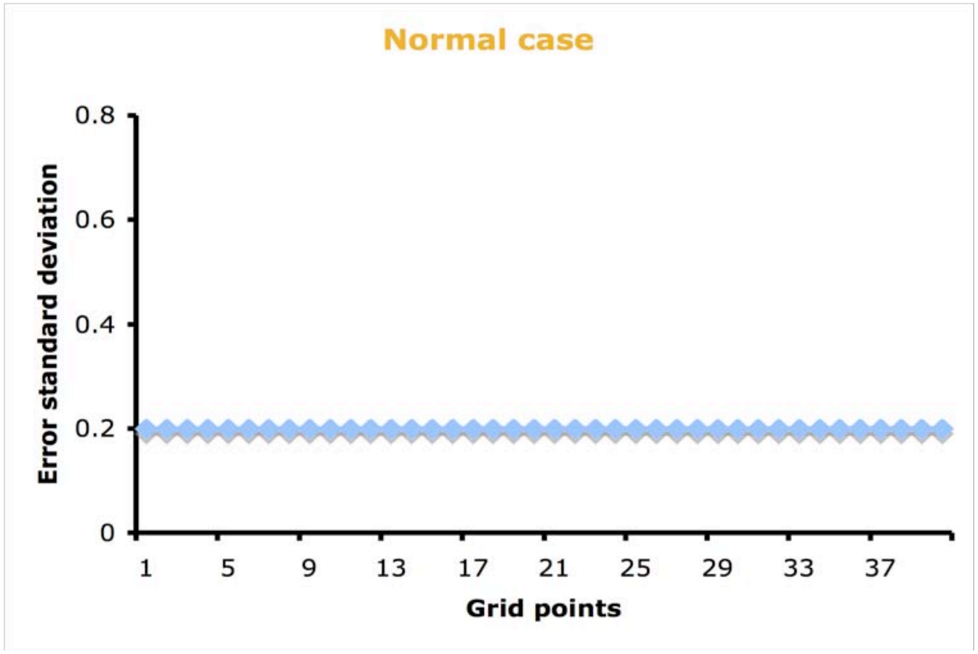
$$\frac{\partial J}{\partial \mathbf{v}_0} = \left[\tilde{\mathbf{K}}_0^T \mathbf{X}_{t|-6}^{fT}\right]\left[\mathbf{e}_{t|-6} + \mathbf{X}_{t|-6}^{f}\tilde{\mathbf{K}}_0 \mathbf{v}_0\right]$$

Forecast error reduction as function of different type observations:

$$J = \left\langle \mathbf{v}_0, \frac{\partial J}{\partial \mathbf{v}_0} \right\rangle = \sum_{i=1}^{n} \left(\frac{\partial J}{\partial v_0^i} \cdot v_0^i \right)$$

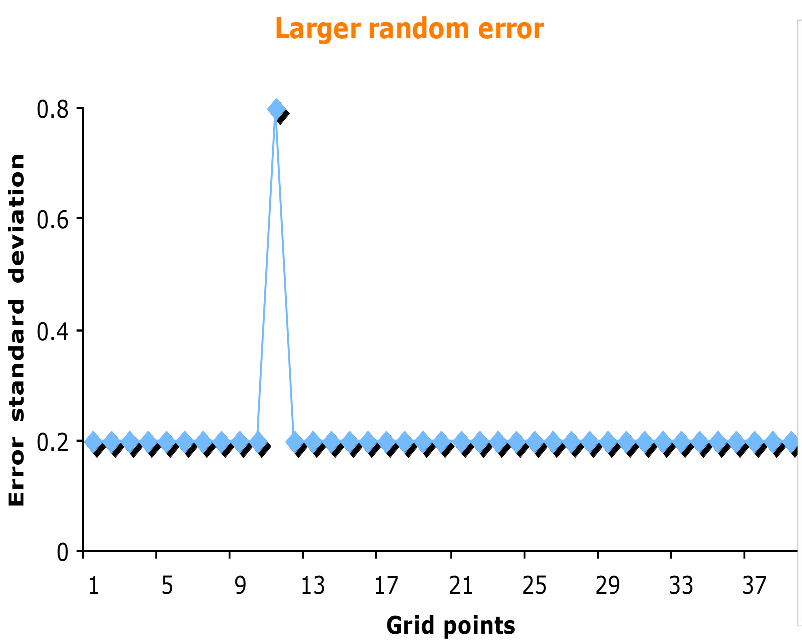
Experimental design

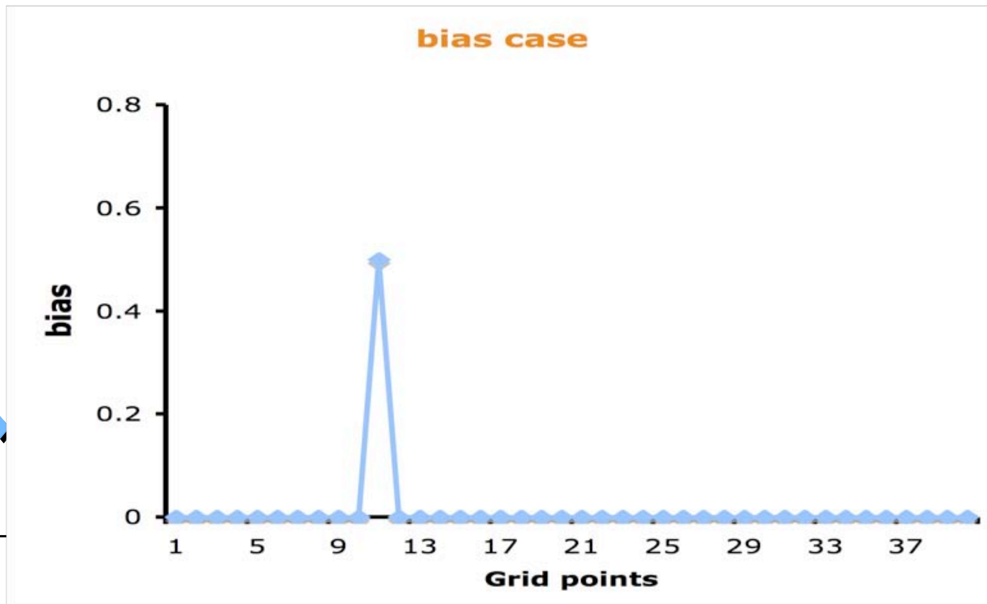
- Model: Lorenz-40 variable model (Lorenz and Emanuel, 1998)
- Assimilation scheme: Local Ensemble Transform Kalman filter (LETKF, Hunt et al., 2007)
- Full observation coverage
- Three experiments:
  - Normal: observation error is 0.2 at every observation location.



Experimental design

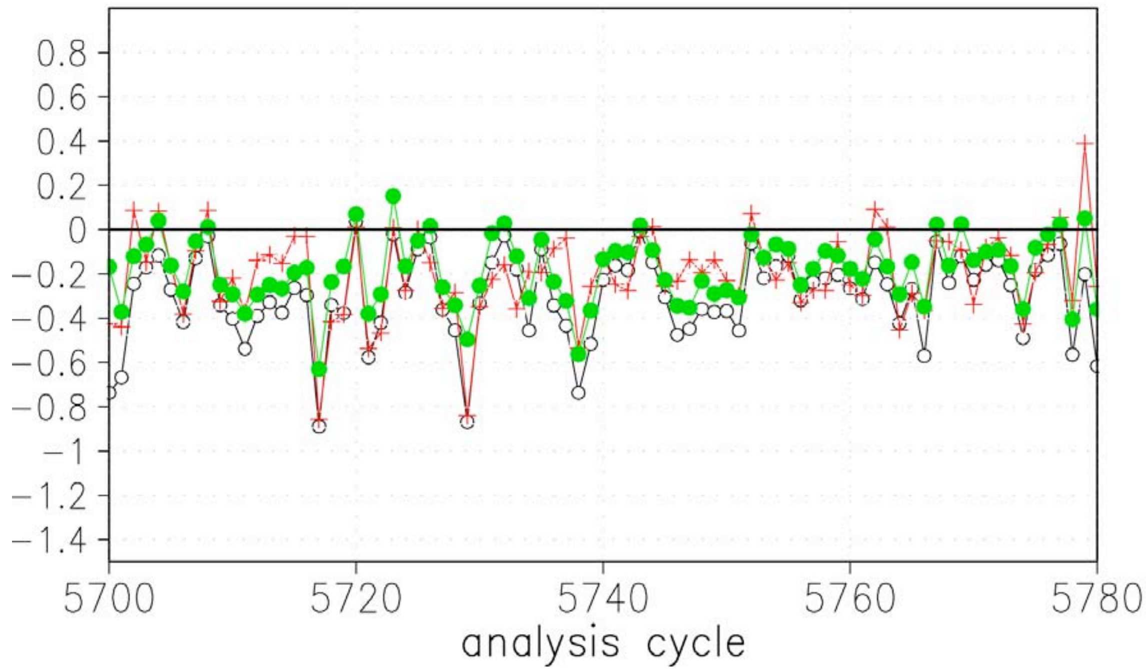
- Three experiments:
  - Normal: observation error is 0.2 at every observation location.
  - Larger random error: SD at 11th grid point is 0.8, but still assume 0.2
  - Bias: the observation at 11th observation location has a bias equal to 0.5.





Observation impact comparison between adjoint method (LB) and ensemble sensitivity method in normal case

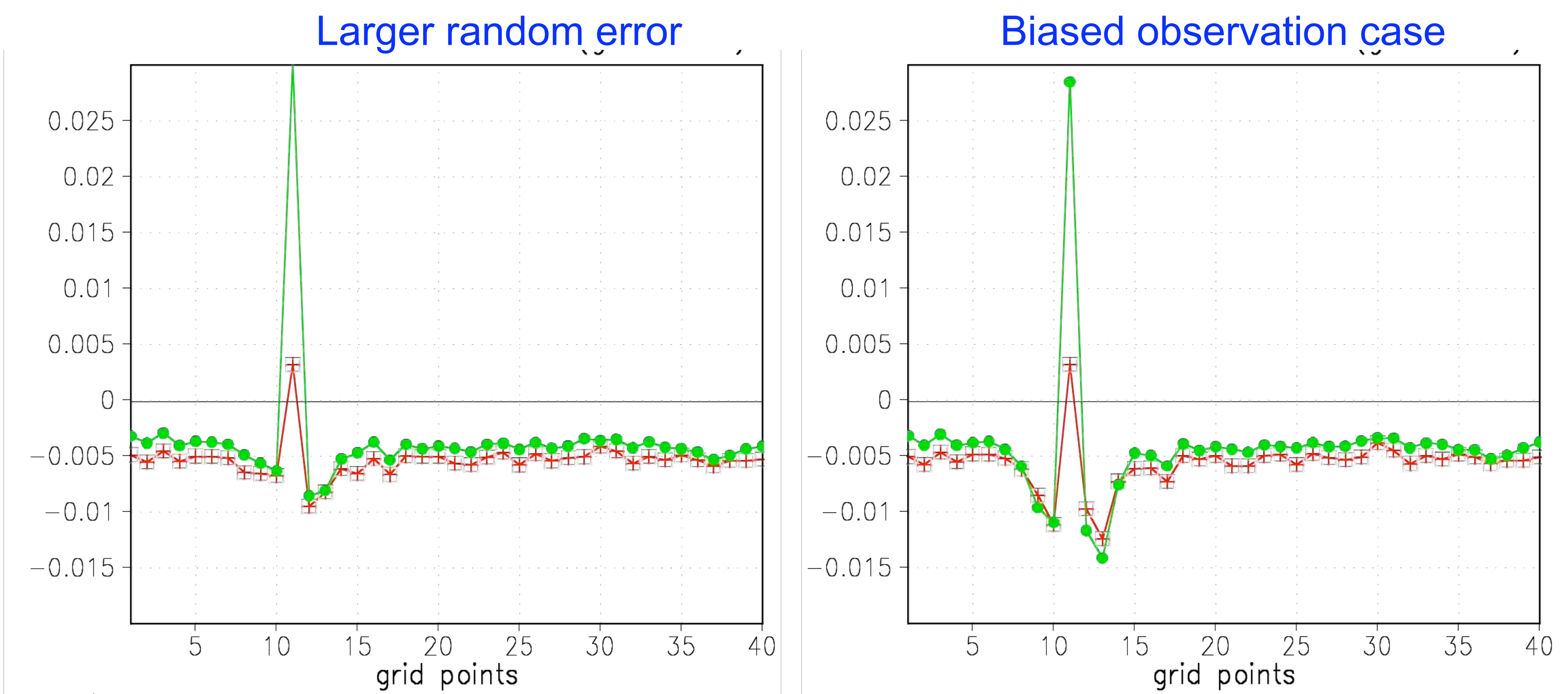
Adjoint method (red), ensemble method (green) and actual forecast error reduction (black)



- ✓ The ensemble sensitivity method gives results similar to the adjoint method
- ✓ Both reflect most of the actual observation impact (black) in the forecast.

Ability to detect the poor quality observation

Observation impact from LB (red) and from ensemble sensitivity method (green)



- ✓ Like adjoint method, ensemble sensitivity method can detect the observation poor quality (11^{th} observation location)
- ✓ The ensemble sensitivity method has a stronger signal when the observation has negative impact on the forecast.

Summary of observation impact study

- *Ensemble sensitivity method calculates the observation impact without using the adjoint model.*
- *Ensemble sensitivity method gives results similar to adjoint method .*
- *Like adjoint method, ensemble sensitivity method can detect the observation which either has larger random error or has bias.*
- *It can show the quantitative forecast impact of any subset of observations without using adjoint model.*
- *It provides a powerful tool to check the quality of the observations.*

Future plans

▪ With the ensemble sensitivity method, and in the framework of ensemble data assimilation, we are going to

— detect the observations which deteriorate the forecasts

— quantify the AIRS observation impact on the forecasts

▪ With the access to the super DOE computers (NERSC), we expect to be able to do more experiments with AIRS data sets.